INVESTMENT PERFORMANCE OF LIFE-SCIENCE VENTURE CAPITAL INVESTMENT FUNDS, PERSISTENCE, AND SUBSECTOR ANALYSIS

By

Jeffrey S. Behrens
A.B. Harvard University, 1989

SUBMITTED TO THE HARVARD – MIT DIVISION OF HEALTH SCIENCES & TECHNOLOGY AND THE MIT SLOAN SCHOOL OF MANAGEMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREES OF

MASTERS OF SCIENCE IN HEALTH SCIENCES & TECHNOLOGY
And
MASTERS OF BUSINESS ADMINISTRATION
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ABSTRACT

Venture capital investment performance data and performance attribution are not typically published. Venture investors articulate (and sell to LPs) conflicting strategies; the popular business literature and culture is rife with rapidly changing beliefs about the relative attractiveness of healthcare venture subsectors, particularly therapeutics and devices. To examine these issues in a more rigorous format I developed a dataset of healthcare venture deals, scored each deal with a new metric ("jb-score"), and assigned each portfolio company to appropriate subsectors.

This dataset was then used to examine subsector performance, persistence, and fund strategy attribution (pure vs. mixed healthcare strategies.) Specifically, I found that the performance characteristics of device and therapeutic (aka biotech or drug) investments are similar: both subsectors evidence similar jb-scores and firms who invest heavily in these subsectors show similar levels of persistent overperformance with devices showing somewhat higher persistence. Firms that focus on one subsector do not perform as well as firms that follow a more balanced strategy.

Finally, I examine the validity of the jb-score and offer some suggestions for future improvements.

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Biographical Note

The author is a graduate of Harvard College (A.B. Philosophy - 1989) and of the MIT Sloan School of Management (M.B.A. 2007). At the time of this writing the author is employed at Biogen Idec, inc. as head of business operations of Biogen Idec's Innovation Incubator and associate director of Biogen Idec's new ventures (internal venture capital fund). This thesis is the final requirement of the author's participation in the joint Harvard-MIT Biomedical Enterprise Program. Previously, the author was founder and president of The Telluride Group, inc, which was sold to mindShift Technologies in 2003. The author may be contacted at jbehrens@sloan.mit.edu for questions regarding this thesis.

I. Introduction

Investing in early stage health-care companies, particularly those that develop drugs and devices, is a challenging and risky endeavor. Compared with IT startups, healthcare startups face significant challenges: a heavily regulated industry, long (multi-year to multi-decade) development and approval timeframes, and tremendous need for capital to support these long and expensive R&D efforts. Furthermore, the state of scientific understanding in healthcare (biology, biochemistry, medicine), although growing rapidly, is still quite far from a thorough understanding and an ability to accurately model and engineer solutions that carry a high confidence of technical success. Much of the cost of drug development comes in expensive human clinical trials where, at the end of the day, what is really going on is hugely expensive trial and error to test if a potential drug does what it is hoped to do (efficacy) without also doing unexpected, unpredicted, dangerous things as well (safety.)

To some extent these more extensive risks and costs are mitigated by the large potential returns for success. A strong patent regime and large potential market sizes make (at least some) successes well worth their risks. A number of venture capital firms have focused, either partially or entirely, on healthcare investing. However there is little public data available on the relative success of these healthcare investors and little data that can shed light on differing investment strategies of venture firms in the healthcare arena.

In the absence of good data there is much discussion and debate in the industry about these various strategies. At issue are the relative attractiveness of different healthcare subsectors (particularly drug and device subsectors), the benefits or drawbacks of firms diversifying investments across healthcare subsectors or between IT and healthcare, and varying beliefs in the cyclicality of these subsectors, the opening and closing of "IPO windows", and growing or shrinking attractiveness of M&A as a viable venture exit.

What makes these questions particularly important is that if venture investors conclude, for example, that early-stage drug investing is not profitable, then this sector may be "starved" for investment and potentially important therapies may languish in academic labs without much chance for advancement. Indeed, the biotech industry often discusses this "funding gap" – academics can find funding for basic research and later-stage (i.e.

clinical-stage) drug companies can also find funding but earlier biotech (pre-clinical) is particularly hard to fund; this funding gap acts as a real barrier to medical progress.

In thinking about some of these questions we can imagine some possible reasons that might explain (or at least partially justify) some of these beliefs. Drugs require substantially more money and time than devices to develop; device development requires different skills (engineering and material science vs. biochemistry and medicinal chemistry.) FDA approval requirements are also different. These differences may create environments where investors who specialize may have advantages; expertise and networks built over time may create information asymmetries and barriers for new investors to enter competitive investment markets successfully. Reputational and related advantages may allow early, successful investors to more easily maintain their dominant positions and thereby receive better dealflow earlier; perhaps stronger human capital skillsets to help sustain their advantages.

This paper attempts to examine in some detail performance of healthcare venture funds at the fund and firm level while also looking within funds to examine investment behavior at the industry sub-sector level. I compare performance of funds that focus on drugs to those focusing on devices and those who follow a blended strategy. I apply a concept and methodology from Kaplan and Schoar (2004) to use persistence as a measure of investor success applied to healthcare funds and subsets of funds that focus on specific subsectors.

Comprehensive data on venture capital fund performance and performance attribution are difficult to find. Venture firms articulate a wide range of strategies for their funds but it can be difficult for outside observers (and perhaps potential limited partners) to validate historical performance of particular strategies. Furthermore, the industry is rife with sets of evolving beliefs that may or may not reflect the realities of the investment challenges venture firms face.

In order to perform this analysis I needed to overcome these limitations using publicly available data. I constructed a measure of deal success ("jb-score") that ranked individual investment decisions a venture firm/fund makes based on the exit status of the respective portfolio company. I ranked IPOs and large M&A exits above modest M&A exits, then undisclosed transaction value M&A exits and finally no documented exit. I calculated this measure for every venture investment in the healthcare industry from 1/1/1990-9/1/2006. I also coded each portfolio company into its appropriate healthcare sub-sector (biotech/devices/services/IT/diagnostics.) Biotech (sometimes called "drug' investing in this paper) and device deals represent the vast majority of healthcare deals; HCIT, diagnostics and services are much less frequently invested in. With this data I was able to calculate relative fund performance and subsector performance for each fund, as well as ascertain how much activity each fund has in the various sub-sectors.

Once constructed, this dataset has enabled answering several key questions about the performance of these funds. Specifically, I was able to demonstrate that the persistence of outperformance in private equity and VC that Schoar and Kaplan found holds true for healthcare investors overall and also holds true for drug and device investors; furthermore, the magnitude of persistence as measured by regression analysis is similar for drugs and devices. Absolute performance as measured by jb-scores was calculated for drugs, devices and the other healthcare subsectors showing similar performance for drugs and devices; better average performance for funds doing many diagnostic deals and weaker performance for funds doing substantial healthcare IT and service deals.

I also compared "pureplay" drug and device funds to mixed funds and saw significantly better performance in the mixed funds. Finally, I provide some evidence that the jb-score is a meaningful, if imperfect, measure of venture performance and offer suggestions on improving this metric.

There are several possible ways to interpret these results -- that over a reasonably long period of time drug and device investing offer similar performance characteristics. First of all in many cases venture firms invest in both sectors and success in either initially may offer future advantages of deal flow and human capital that benefit both sectors. Skillset requirements may be similar across both of these subsectors; or perhaps networks required to be successful (medical and scientific) may overlap significantly. Finally, the evidence that blended funds outperform pure healthcare funds may be explained by the ability of blend-style investors to select exit timing across sectors and take advantage of M&A and IPO market cyclicality, effectively giving blend-style investors more opportunities for successful exits than pureplay investors.

II. Motivating Questions and Relevant Literature

A. Popular culture context

In conversations with several of the principals of life science venture capital firms I heard very different views on investment strategy. In some cases, investors who had previously spent a great deal of time with early-stage drug investing were now disillusioned and moving more efforts into device investing and later-stage drug deals. They would make statements that basically argued that it was impossible to be successful as a venture investor in drug investing and that device investing was a better, safer place to "bet." Two quotes illustrate some of these tendencies:

> "We're not going to do any more early stage therapeutics investing"
> – Ellen Baron, Partner, Oxford Biosciences

> "The VCs are getting tired…" (…with drug investing)
> – Dave McLachlan, former CFO, Genzyme

A quick scan of the popular business literature easily identifies many such themes – are there fundamental changes in the world that successful investment strategies should take into account? Some quick examples illustrate this clearly – for example, trends appear to swing between favoring biotech and favoring devices:

> "Biotechnology, considered the darling investment sector of the high rollers in the early 1990s, seems to have fallen by the wayside, and investors are now wondering what kind of future this sector holds." VC Journal "Why Tech VCs Have Left Biotech" 8/1/99

> "A healthy increase in venture-capital funding of medical-device companies has helped lift overall investments in life-sciences industries, even as biotechnology deals have tailed off." Peter Loftus 2/3/06 WSJ

Other articles question whether there are substantive differences in the overall risk profile of device investing when compared to drug investing, as the following quote illustrates:

> "Medical device investing has been the "Steady Eddie" of venture capital; and also it's Rodney Dangerfield. On Sand Hill Road, especially in the heady Internet days of the late 1990s, medical device entrepreneurs could hardly get a meeting, never mind respect. Many top-tier VCs either de-emphasized or completely shut the door on life science investing. Today, we realize that information technology (IT) and biotech valuations fall as fast as they rise, and those seasoned, rock-solid medical device entrepreneurs who've been waiting in the lobby are looking better by the day." VC Journal "TechTalk: Hitting Singles and Doubles With Medical Technology" 12/1/2002

The following illustrates questions regarding the benefits of funds that focus on subsectors versus diversify across them:

> "The era of the generalist venture capitalist is over. Specialized funds are a logical extension of the continued evolution of both health-care and information technology investing. Not everyone can be an expert in every subject." VCJ 8//1/99 "Why Tech VCs Have Left Biotech"

What I take away from these popular business culture "datapoints" are a number of questions about investment strategy and performance:

- Is there a clear advantage in drugs or device investing?
- Do pure-play drug or device investors perform better than blended funds?
- Do these answers change over time in a cyclical fashion, perhaps correlated to overall market conditions?
- To what extent does casual conversation and popular culture reflect the data-supported realities of fund behavior and performance?

B. Academic Literature on Venture Capital Performance in Life Science Sub-sectors

Much of the limited academic work on the venture capital business tends to focus on the overall industry (or even includes the broader set of private equity firms with venture capital.) Due to the paucity of publicly available research and fund reticence to share investment strategies, research is hard to perform.

Although there is relatively little direct research reported in the literature on venture capital performance of life science sub-sectors, the following three articles address relevant topics in venture capital performance and use methods that have applicability in this area.

Gompers, Kovner, Lerner, Scharfstein 2005 (Gompers et al.)

> Gompers et al. examine patterns of venture capital investments and performance and their relationship to public market (IPO) patterns. They use similar methods to those used in this paper to both organize a dataset of venture investments into 9 industries (one of which is healthcare) and to score the relative success of investment outcomes in a binary fashion (M&A or IPO = success; otherwise = failure).
>
> Gompers et al. show that industry-experienced venture investors increase their rate of investing in that industry in response to increased IPO activity in that industry and do not suffer performance penalties for this change in investment behavior. They are trying to disentangle rational investment behavior based on market signals (IPO rates) vs. irrational (or at least inefficient allocation of capital) investment choices that demonstrate "herd" behavior.
>
> Gompers' results bolster the idea that experienced/successful healthcare blended-fund investors who invest in both drug and device deals may be able to take advantage of IPO windows rationally; however his analysis leaves open a number of questions.

Because their industry groupings are fairly broad (i.e. the authors do not separate medical devices vs. biotechnology) they conflate subsector performance that might be negatively correlated. In addition, their measure of success can be criticized because by scoring all M&A transactions as a success they risk over-counting successful exits. In many cases (and particularly when M&A transaction values are non-disclosed) M&A transactions are not successful exists for venture investors and may not return much (if any) capital to the venture partnership. In our analysis below, we use a ranked scoring system to rank M&A exists on transaction size and only score undisclosed transactions as marginally better than no transaction at all in an attempt to more accurately characterize venture outcomes of M&A transactions.

Kaplan & Schoar, 2004

Kaplan & Schoar demonstrated persistence in private equity fund performance - a key measure of long-term investment success that is not apparent in public mutual fund performance. They dismissed selection bias, risk differences, and industry differences as possible explanations and instead argue that differences in partner skill, deal flow access, better deal terms, and access better management account for this persistence in performance. One key question left unanswered is what accounts for first fund success – one could easily argue that with a strong first-fund track record, venture firms can more easily attract all of the human and deal resources identified by Kaplan & Schoar and thereby maintain their performance advantages over time. However it is equally plausible that initial fund success is a random (if once achieved thereafter sustainable) event that occurs before differentiating resources are acquired by the venture firm.

Kaplan & Schoar's argument lends credence to the idea that successful venture investing is based on skill and related resources vs. random luck. This paper applies this methodology to healthcare subsectors and shows that skill continues to play a role in investment success through persistence of fund outperformance; and that the quantitative amount of persistence is similar for drugs and devices.

Kaplan & Schoar, like Gompers et al above, also use broad industry classifications and do not divide healthcare into subsectors which could play an important role in performance attribution. Choices of specific subsectors as well as subsector specialization could both be possible source of performance attribution and this paper attempts to explore this line of inquiry.

Lerner, 1994

In this paper, Josh Lerner discussed the decision for venture firms to take biotechnology portfolio companies public. He distinguishes the behavior of less- and more-experienced venture investors in taking their portfolio companies public at times at or near peaks public markets (measured by an index he constructs of public biotech companies and proxies) and demonstrates that more seasoned investors are "particularly proficient at taking companies public at market peaks."

This paper provides some of the possible underlying reasons why there is persistence of overperformance in venture capital and points directly to experience level of investors and their ability to achieve successful exits as critical expanatory factors in persistence of overperformance.

Of particular note in this paper is his methodology in constructing his datasets. For example, he uses the age of the oldest VC fund in a company as a proxy for experience. It would be interesting to apply his approach and compare device vs. drug investing to see if the patterns he finds in drug (biotech) investing hold true in devices, where development cycles are much shorter, capital requirements are smaller, and historically there has been a more robust M&A market for these firms to exit successfully.

III. Data – Sources, Analysis, Methodology

A. Data Sources:

To develop the dataset used in this study the following sources of data were used:

- Thompson Financial SDC Platinum downloads: rounds, funds, firms, portcos (no return data at the fund level): http://www.thomsonib.com/sp.asp. This source is made available to all MIT students through the Dewey Business Library.
- Private Equity Intelligence (fund return info but only for ~1/3 of HC funds; no round/investment info): http://www.prequin.com/. This is a costly database; I contacted the owners of the firm and requested access as a form of sponsorship with was granted for a 30 day period to enable me to download a "snapshot" of PEI's data this summer.
- Jay R. Ritter's IPO data: http://bear.cba.ufl.edu/ritter/ipodata.htm, Cordell Professor of Finance at the University of Florida. This data is publicly and freely available on Ritter's website.

B. Methods:

1. Overall Strategy and Limitations

Evaluating venture capital firm and fund performance, and attempting to relate fund performance to investment strategy, is challenged by limitations in available data. Thompson's SDC data does provide round-level investment information. This effectively tells us, for every round that a venture firm/fund participates in, what type of company received the investment, how many investors participated, and the total size of the round. However we cannot consistently find the allocation of the round to the various funds participating and therefore need to make several assumptions to perform subsector analysis and performance attribution. We do not know the capitalization structure of portfolio companies and the corresponding % holdings of the investors.

PEI sells a regularly updated dataset of fund-level performance statistics (and was willing to provide this data for this study as a sponsor.) However, of the funds we identified with significant investments in healthcare, only about 30% were found in the PEI dataset.

Additional exit information is available in Thompson's SDC Platinum. We can identify every portfolio company's exit data if an exit occurred. Specifically, in the case of an IPO we have the date and financial characteristics of the IPO. With M&A exits in some cases the deal value is disclosed, but in many cases it is not.

Therefore we need to make a number of simplifying assumptions in order to carry out this analysis which can introduce error and noise into our datasets:

- We assume that in every round, all investors participate equally. Although this clearly does not reflect the reality of investments, round distributions are not public. Funds that have small "sidecar" entrepreneur funds that co-invest with main funds may lead to overcounting subsector participation for particular firms; given the size of the dataset I suspect that such effects will be similar across subsectors and not introduce subsector-favoring bias to the following analysis.
- We assume that for most undisclosed M&A exits acquired by public companies, the value of the transaction must be low enough to be not meaningful to the acquirer, and therefore not a strongly successful exit for the investors. There may be a small number of cases on an acquisition by a very large acquirer that is undisclosed but still large enough to be a success for the venture investors. In addition, at times a later investor may invest at a time of desperation, cram down previous investors, and be the only investor to see a successful exit upon a sale. Due to the lack of detailed exit information I cannot overcome these limitations but do not believe they are numerous enough to affect the conclusions; and in any case I believe this bias is a better one to incur than to make the opposite assumption (as per Gompers et al 2005) where the authors count every M&A exit as a success independent of valuation amount or disclosure status.

- We developed a scoring algorithm (described below) that scores every "round" that a fund participates in based on the assumed return from the exit (if any.)
- We scored every separate investment into a portfolio company by a fund separately and gave each "bet" equal weighting. If a fund made multiple investments in a single portfolio company each investment was score independently, representing the idea that a fund makes an independent decision at each round, and can always decide to stop participating in future rounds. (Ideally, it would probably be more accurate to weight follow-on rounds somewhat lower than initial rounds in a future revision of the jb-score.)

In a later section of this paper this measure is evaluated and several suggestions are made regarding possible improvements to this methodology for future study.

2. Building the dataset

On 10/22/2006 I downloaded 49,469 VC investment rounds from SDC Platinum with round dates between 1/1/1990 and 9/1/2006 in the healthcare industry sector. (see appendix 1 for industry code search criteria) Each round included data on the investor fund & firm, date, total round amount (note: individual fund allocation of the round was not available), portfolio company name & industry and other descriptive information. I developed a lookup table to code each rounds' portfolio company into healthcare industry sub-sectors (biotech, devices, healthcare IT, heathcare services, diagnostics) – See Appendix 2 for this table.

SDC data also includes portfolio company IPO data and amount (if any) and acquisition dates and value (if any.) Each portfolio company was then scored on its exit as follows:

Exit	Score
IPO	4
M&A >$100m	4
M&A <= $100m	3
M&A < $50m	2
M&A undisclosed	1
No exit	0

Each of the 49,469 rounds was then scored based on the exit score of its corresponding portfolio company (0-4.) Totals were calculated for each venture capital fund for all of that funds deals, as well as subtotals for each HC industry sub-sector (biotech, devices, etc…) Total numbers of rounds each fund participated in were counted. A "jb-score" ("Jeff's VC performance score") was calculated for each fund for each HC subsector and HC investments overall by dividing the total scores by the number of rounds that firm participated in. These jb-scores range from 0 to a "perfect" 4.

To examine cyclical effects I calculated average jb-scores for each year for all healthcare deals and then used these annual averages to normalize jb-scores for each fund in each subsector and in HC overall.

In each healthcare sub-sector (biotech, devices, etc…) funds with >4, 5 or 9 rounds (depending on the total number of funds in that subsector) were ranked and assigned to quintiles (quartiles in the case of healthcare diagnostics and healthcare IT.) This was done for both raw and normalized jb-scores.

Transition matrices were generated for each subsector and healthcare overall in the following format. These matrices score firms that have multiple funds over time with fund N along the vertical and fund N+1 along the horizontal. This provides strong evidence of persistence of overperformance when the percentages along the diagonal (1->1 for example) are much higher than a random distribution which would be ~20%.

biotech_quint

	1	2	3	4	5
1	24	7	1	2	1
2	12	17	7	4	1
3	5	16	21	4	0
4	5	10	14	10	5
5	2	8	8	8	7

	1	2	3	4	5
1	68.6%	20.0%	2.9%	5.7%	2.9%
2	29.3%	41.5%	17.1%	9.8%	2.4%
3	10.9%	34.8%	45.7%	8.7%	0.0%
4	11.4%	22.7%	31.8%	22.7%	11.4%
5	6.1%	24.2%	24.2%	24.2%	21.2%

biotech_quint_norm

	1	2	3	4	5
1	19	9	4	2	5
2	13	15	13	7	3
3	10	12	11	8	3
4	4	10	10	6	7
5	4	2	5	6	11

	1	2	3	4	5
1	48.7%	23.1%	10.3%	5.1%	12.8%
2	25.5%	29.4%	25.5%	13.7%	5.9%
3	22.7%	27.3%	25.0%	18.2%	6.8%
4	10.8%	27.0%	27.0%	16.2%	18.9%
5	14.3%	7.1%	17.9%	21.4%	39.3%

Finally, regressions were performed with Microsoft Excel's LINEST function for each subsector – regressing fund N+1 as the "Y" variable to fund N as the X. This was done for both raw and normalized jb-scores. A 2-variable regression of fund N+1 to both fund N and the year 3-6 moving average count of IPOs (from Ritter) was done to look for the role of cyclical effects.

C. Descriptive Statistics:

The dataset was downloaded from SDC Platinum via MIT's Dewey Library. I downloaded all healthcare venture capital investments from 1/1/1990-9/1/2006 (appendix 1 lists the industry codes used to identify these deals) and coded investments by the industry and subsector of each respective portfolio company (appendix 2 shows the coding methodology) which incorporated 1076 venture funds and 6894 portfolio companies. In Chart 1 below, 935 funds made biotech investments and 1001 funds made device investments. These two groups of funds have very similar "jb-scores" and similar volatility of the jb-score which implies that the performance of funds in these sub-sectors does nor differ substantially during the time period measured in this dataset. Diagnostics does appear to have both a much smaller number of funds investing in the sub-sector and a higher average jb-score (1.39) and more volatility than biotech and devices. Services and HC appear to perform less less than biotech and devices overall.

Chart 1: Descriptive Statistics

	Biotech		Device		Diagnostics		HCIT		Services		ALL HC	
		STD		STD		STD		STD		STD		STD
Number of funds	935		1001		178		103		257		1076	
Average j-score	1.18	1.08	1.22	1.11	1.39	1.48	1.00	1.10	0.94	1.07	1.11	0.93
Average normalized j-score	0.38	0.91	0.32	0.93	0.35	1.3	0.04	1.03	-0.14	0.95	0.24	0.74
Total rounds	9,207		10,194		1,269		818		2,788		26,981	
Total j-score	10,852		12,953		1,891		821		2,693		31,653	
Total calculated j-score/rounds	1.18		1.27		1.49		1.00		0.97		1.17	

(note: number of funds do not total as many funds have substantial investment activity across multiple subsectors.)

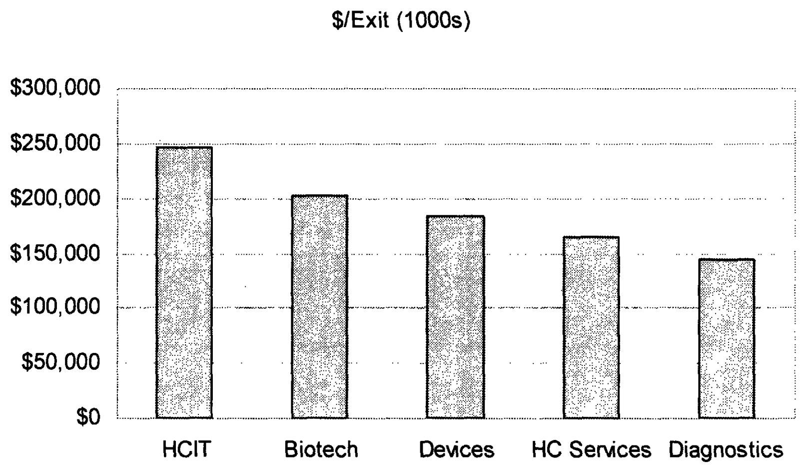
Although most of the analysis in this paper is performed at the venture capital fund level, it was interesting to look at the source data at the portfolio company level. The following chart calculates (in the last column) the number of companies funded per successful exit (M&A with reported valuation >$100m or an IPO) and a notable difference is seen between subsectors with biotech and device once again being the strongest areas (and very close) wereas services and hcit appear to be the most "risky" companies from the perspective of likelihood of a successful exit.

Chart 2: Companies per exit

	Num Cos	M&A	IPO	total	co/exit
biotech	2122	40	179	219	9.7
device	2300	53	171	224	10.3
diagnostics	537	9	32	41	13.1
services	1340	42	59	101	13.3
hcit	595	17	22	39	15.3

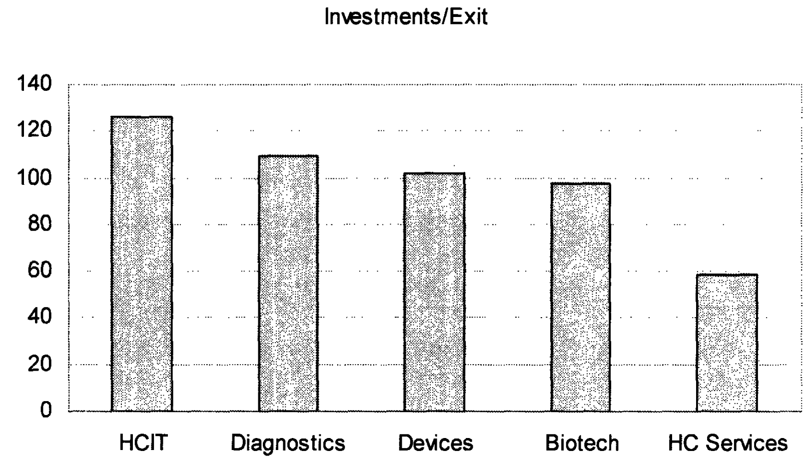
I performed a similar analysis at the company level to examine $ invested in portfolio companies and compared this total amount of investment to the number of successful exits to determine the average "cost" to a successful exit.

Chart 3: $/Exit



I then examined the number of investments made by venture firms in each sector, where an investment was defined as each time a firm invests money in a round. (So a single round with multiple investors generates multiple investments.) This counting of individual investment decisions (or "bets") is also the methodology used in quantifying the investment activity level of venture funds in the various sub-sectors of heathcare. Chart 4, below, show the number of investments per successful exit in each subsector.

Chart 4: Investments/Exit



Finally, I examined investment fund strategies relating to the fund investment composition mix. Life sciences venture funds follow a subsector strategy – and along with selecting one or more subsectors, a firm can choose to follow a more "pure" strategy or one where it balances investments across multiple subsectors.

This chart below compares performance of mixed funds vs. biotech and device specialty funds. I used actual investment history as the criteria to define fund strategy – if a fund invested in 8 or more rounds in both devices and biotech (and had >75% of its total rounds in these areas) then I defined it as a mixed strategy; I defined pure strategy as >60% of rounds falling into one of the subsectors.

The results of this analysis demonstrate a strong benefit in a mixed strategy with a very strong improvement in average Jb-scores. Biotech-pure strategies provide the poorest returns; and the variance of the mixed strategy is also the lowest on a relative basis.

Chart 5: Comparing pure vs. mixed subsector strategies

	AVG	STD	Num	Notes
mixed fund (all)	1.20	0.85	61	1,2
pure bio >8 rounds	0.76	0.66	74	1,3
pure device >9 round:	0.94	0.83	38	1,4

1 j-scores for ALL rounds fund invested in
2 >75% of rounds are biotech or device and >8 rounds biotech and device
3 >60% rounds are biotech
4 >60% rounds are device

D. Persistence/Regressions:

Kaplan and Schoar (2004) focus on persistence of overperformance as a key signal of investor skill in determining long-term firm performance. I was interested in using this measure to ask a slightly different question – if we examine persistence across different subsectors of health-care investing, do we see meaningful differences in persistence; and if we do, perhaps we can interpret this as evidence in the nature of the investment thesis in that specific subsector. By combining evidence on persistence with the above identified statistics on overall sub-sector specific fund performance in the descriptive statistics, I hoped to be able to rationally, and in an evidenced-based manner, compare investment thesis across healthcare subsectors.

I performed three regressions for each healthcare industry subsector. "Raw" regresses jb-scores for fund n+1 to fund n. "Norm" regresses the normalized jb-scores for fund n+1 to fund n (where normalization is as above – subtracting average annual healthcare jb-scores from each value.) "Raw + IPO yr" regresses fund n+1 to 2 possible explanatory variables – the average IPO count for the year (from Ritter, a moving average of years 3-6 offset) and fund n. This third regression is a check to see to what extent subsector performance is explained by overall industry performance and serves as an alternate method to examine this from examining the normalized regressions.

Some of the key observations in the "raw" data are that in all subsectors we see strong evidence of persistence – the larger the coefficient the stronger the persistence effect. Standard errors are appropriately low for all subsectors but healthcare IT to provide confidence in these measures. We see a fairly strong difference in the persistence measure for biotech to devices (.23 to .44) which is weakened considerably when looking at normalized numbers (.18 to .23). When regressed to the IPO count as well as to the raw fund performance this difference in effect almost disappears (.16 to .17).

Chart 6: Regressions

		biotech	device	diag	hcit	services	all hc
	Coefficient	0.23	0.44	0.51	0.23	0.85	0.52
	Std err	0.05	0.06	0.13	0.29	0.27	0.04
Raw	R^2	0.07	0.20	0.24	0.04	0.33	0.27
	F-val	18.20	54.82	15.55	0.64	23.92	189.47
	Coefficient	0.18	0.23	0.33	0.18	0.29	0.29
	Std err	0.05	0.06	0.13	0.27	0.09	0.04
Norm	R^2	0.06	0.06	0.13	0.03	0.09	0.10
	F-val	14.69	13.63	6.89	0.45	9.82	54.47
	Coefficient	0.32	1.04	1.54	0.29	0.85	0.82
	Std err	0.16	0.17	0.47	0.96	0.27	0.09
Raw +	Coefficient	0.16	0.20	0.30	0.20	0.34	0.29
IPO yr	Std err	0.06	0.07	0.13	0.31	0.10	0.04
	R^2	0.08	0.32	0.39	0.04	0.33	0.36
	F-val	11.20	51.19	14.86	0.34	23.92	147.88

As a check to examine to possible role public market performance (in particular, new IPOs) might drive some of the performance of healthcare venture investing, I regressed biotech and device performance to the number of IPOs/year from Ritter. As before, for IPO/year I take the first investment date of the fund to define vintage year and then look at the IPOs 3-6 years out to get a moving average. This of course shows no correlation; i.e. annual IPO performance is not predictive of biotech and device performance.

Chart 7: Subsector raw Jb-scores to IPO count regressions

	biotech	device
Coeff	0.00	0.00
Std Err	0.00	0.00
R^2	0.12	0.23
F-value	26.21	55.43

A somewhat more intuitive way to visualize this data, also used in Kaplan and Schoar (2004), is the construction of transition matrices. To construct a transition matrix I grouped funds into quintiles (quartiles for diagnostics and HCIT due to the paucity of funds doing a meaningful number of transactions.) I then looked at fund n to fund n+1 transitions (i.e. how often a fund n was in the 1st quintile was followed by a fund n+1 that was also in the 1st quintile.)

In the charts below I shaded matrix elements along the diagonal that are well above expected values from a random distribution. What is particularly striking is that we see strong persistence in the better-performing funds (1st & 2nd quintiles) with much weaker persistence in the poorer-performing funds. I suspect this may be due to survivorship bias (the weakest funds have trouble raising follow-on funds.)

Chart 8: Transition matrices

Biotech

Transition Matrix/Raw

	1	2	3	4	5
1	68.6%	20.0%	2.9%	5.7%	2.9%
2	29.3%	41.5%	17.1%	9.8%	2.4%
3	10.9%	34.8%	45.7%	8.7%	0.0%
4	11.4%	22.7%	31.8%	22.7%	11.4%
5	6.1%	24.2%	24.2%	24.2%	21.2%

Transition Matrix/Normalized

	1	2	3	4	5
1	48.7%	23.1%	10.3%	5.1%	12.8%
2	25.5%	29.4%	25.5%	13.7%	5.9%
3	22.7%	27.3%	25.0%	18.2%	6.8%
4	10.8%	27.0%	27.0%	16.2%	18.9%
5	14.3%	7.1%	17.9%	21.4%	39.3%

Devices

Transition Matrix/Raw

	1	2	3	4	5
1	48.4%	35.5%	3.2%	6.5%	6.5%
2	38.1%	28.6%	26.2%	7.1%	0.0%
3	25.6%	25.6%	25.6%	18.6%	4.7%
4	14.3%	5.7%	54.3%	17.1%	8.6%
5	2.9%	17.6%	38.2%	8.8%	32.4%

Transition Matrix/Normalized

	1	2	3	4	5
1	35.1%	27.0%	18.9%	5.4%	13.5%
2	28.6%	35.7%	11.9%	11.9%	11.9%
3	8.6%	20.0%	37.1%	17.1%	17.1%
4	14.9%	17.0%	27.7%	23.4%	17.0%
5	29.2%	16.7%	20.8%	0.0%	33.3%

Diagnostics

Transition Matrix/Raw

	1	2	3	4
1	57%	29%	0%	14%
2	17%	67%	17%	0%
3	0%	0%	50%	50%
4	0%	0%	0%	100%

Transition Matrix/Normalized

	1	2	3	4
1	50.0%	33.3%	0.0%	16.7%
2	22.2%	44.4%	11.1%	22.2%
3	0.0%	0.0%	83.3%	16.7%
4	0.0%	0.0%	0.0%	100.0%

HCIT

Transition Matrix/Raw

	1	2	3	4
1	0.0%	100.0%	0.0%	0.0%
2	0.0%	100.0%	0.0%	0.0%
3	66.7%	0.0%	33.3%	0.0%
4	66.7%	0.0%	0.0%	33.3%

Transition Matrix/Normalized

	1	2	3	4
1	50.0%	50.0%	0.0%	0.0%
2	0.0%	100.0%	0.0%	0.0%
3	40.0%	20.0%	20.0%	20.0%
4	100.0%	0.0%	0.0%	0.0%

All HC

Transition Matrix/Raw

	1	2	3	4	5
1	57.1%	14.3%	21.4%	0.0%	7.1%
2	29.4%	52.9%	17.6%	0.0%	0.0%
3	18.8%	25.0%	18.8%	25.0%	12.5%
4	0.0%	19.0%	19.0%	57.1%	4.8%
5	12.5%	25.0%	25.0%	12.5%	25.0%

Transition Matrix/Normalized

	1	2	3	4	5
1	25.0%	33.3%	25.0%	16.7%	0.0%
2	25.0%	35.0%	15.0%	15.0%	10.0%
3	17.4%	21.7%	26.1%	26.1%	8.7%
4	15.4%	23.1%	7.7%	30.8%	23.1%
5	12.5%	12.5%	0.0%	12.5%	62.5%

IV. jb-score Justification, Validation and Possible Improvements

As was discussed in the methods section, above, the Jb-score is a calculated measure of venture investment performance at the portfolio company level. The construction is to score every "bet" a venture fund makes in a company round with a number from 0 to 4. This has the advantage of enabling dissection of fund performance to the individual portfolio company level or any rational grouping of portfolio companies. This paper primarily groups portfolio companies based on industry sector and subsector; this analytical method would support other grouping that could include other factors (stage of investment, round #, size or rounds, dates of rounds, etc…)

I had to use this measure (similar to Lerner's methology in his 1994 paper) as return data is not available at the portfolio company level. PEI provides fund IRRs but only has sparse coverage of funds that focus on health care venture investing. Furthermore, by being able to relate Jb-score performance measures to number of investments in subsectors we can rationally filter out small numbers of investments in a particular subsector and focus on where venture funds/firms actually invest compared to where they say they invest.

To validate this method I looked at two different statistical tests. First, I examined the correlation of the jb-score to Ritter's IPO counts. I first examined correlations for all HC funds and all funds by vintage year (defined by the year of the first investment of the fund). As venture performance is driven by exits which typically occur several years after the vintage year of the fund, I examined offsetting the IPO count average by 0-8 years and found the best correlations between 3-4 years (.57 to .63). By calculating a moving average of years 3-6 offset, the correlations rose to .63 and .66; a strong correlation and good evidence that the jb-score is capturing meaningful performance data for individuals funds (under the assumption that venture fund performance is correlated to IPOs.)

Chart 9: Ritter IPO Counts to Jb-score Correlations

	Ritter IPO Counts	
offset	HC	ALL
0	0.48	0.46
1	0.49	0.51
2	0.55	0.57
3	0.57	0.63
4	0.60	0.63
5	0.56	0.52
6	0.38	0.38
7	0.39	0.38
8	0.29	0.29
yr 3-6 avg	0.63	0.66

Secondly, I obtained venture capital benchmark performance data from SDC platinum by year and calculated a correlation between these benchmarks and the jb-score for both healthcare and all venture funds. The results here are not quite as strong as the Ritter correlations but are still above .5.

Chart 10: Testing the jb-score to HC and all VC

0.5124	corr HC to VC
0.5145	corr all to VC

These results give some direction to possible future improvements in the jb-score. Given the better correlations with Ritter's IPO data than with venture capital performance benchmarks we may be over-valuing IPOs as successful exits and could look at IPO valuations to more carefully calculate the jb-score as we do with M&A transactions (i.e. score post-money valuations >$200m as 4, >$100m as 3, etc…) A number of different algorithms could be developed and then tested against VC benchmarks and Ritter's IPO data to identify the best algorithm for refining the jb-score.

V. Conclusions

This thesis explores venture capital investment performance in healthcare and healthcare subsectors including therapeutics and devices. I constructed a dataset of healthcare venture capital investment transactions and coded these with industry subsector and a measure of investment outcome ("jb-score") that scores IPO and M&A exits. Totals for number of transactions in each subsector and corresponding total jb-scores were calculated for each venture capital fund. The dataset was then analyzed to measure persistence of overperformance of funds that invest in various subsectors and this amount of persistence was compared across sub-sectors. As in Kaplan and Schoar (2004), overall healthcare as well as therapeutics and device investors demonstrate persistence in overperformance; with strongest overperformance in the device subsector. Average jb-scores were compared across subsectors to give a measure of overall success in investments in each subsector; variance is similar across subsectors except for healthcare IT where variance is much larger than the other subsectors. Additional measures were calculated that include # of portfolio companies per successful exit, $ invested per successful exit and investments per successful exit to further explore differential investment performance of healthcare subsectors.

Across all of these analyses there is little different in the behavior of device and therapeutics beyond a slightly stronger persistence signal mentioned above. It appears that over the time period examined (1990-2006) the long-term performance of these subsectors is quite similar. Furthermore, it appears that funds that invest in both sectors perform better than focused funds that invest more than 60% of the time in a single subsector.

The jb-score's validity was explored through a series of regressions against annual IPO counts and annual benchmark venture capital performance; the jb-score appears to correlate well with these benchmarks providing a strong validation for this constructed measure.

VI. Bibliography

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APPENDICES

1. SDC Search Criteria
2. Health care industry subsector coding table
3. IPO counts from Ritter, years 3-6 from fund vintage year

Appendix 1: SDC health care investments industry search criteria

2820 Medical/Health
2825 Scientific Products
2840 Medical/Health Services
2845 Scientific
2860 Medical/Health Info/Content
2865 Scientific Info/Content
4111 In Vitro Monoclonal Antibody Diagnostics
4112 In Vivo Monoclonal Antibody Diagnostics/Imaging
4113 DNA/RNA Probes
4119 Other Medical Diagnostic Biotechnology
4121 Therapeutic Monoclonal Antibodies
4122 Immune Response Effectors (interferons, vaccinations)
4123 Other Therapeutic Proteins (incl. hormones)
4129 Other Therapeutic Biotechnology
4130 Genetic Engineering
4311 Biotech Related Fine Chemicals (NOT Pharmaceu
4312 Biotech Related Commodity Chemicals
4319 Other Biochemical Products
4321 Biotech Related Food Enzymes and Cultures
4322 Biotech Related Food Diagnostics
4329 Other Biotech Processes for Food Industrial Products
4525 Biotech laser and optronic applications
5121 X-Rays
5122 CAT Scanning
5123 Ultra Sound Imaging
5124 Nuclear Imaging
5125 Other Medical Imaging
5221 Surgical lasers (including laser delivery fib
5412 Long Term Care/Home Care/Elder Care
5414 Dependent Care (child care/assisted living
2735 Medical/Health Software
2741 Scientific Software
3710 Chromatographs & Related Laboratory Equipment
3720 Other Measuring Devices
3799 Other Analytical & Scientific Instrumentation
4110 Medical Diagnostic Biotechnology Products
4120 Therapeutic Biotechnology Products
4210 Genetically Engineered Plants
4220 Genetic. Eng. Microorganisms to raise plant yield
4230 Other Plant Related Biotechnology
4240 Biotech Related Animal Health & Nutrition Products
4250 Genetically Engineered Animals
4290 Other Animal Related Biotechnology
4310 Biochemical Products
4320 Biotech Processes for Food Industrial Applications
4330 Biotech Processes for Pollution/Toxic Waste Contrl
4340 Biotech Processes for Enhanced Oil Recovery/Mining
4390 Other Industrial Biotechnology
4410 Biosensors for Medical Diagnostic Applications
4420 Biosensors for Industrial Applications
4490 Other Biosensors
4510 Biotech Related Analytical Instruments & Apparatus
4520 Biotech Related Production Equipment
4599 Other Biotech Research & Production Equipment
4610 Pure & Contract Biotechnology Research
4699 Other Biotechnology Services
5110 Diagnostic Services
5120 Medical Imaging
5130 Diagnostic Test Products & Equipment
5140 Other Medical Diagnostics
5210 Therapeutic Services
5220 Surgical Instrumentation & Equipment
5230 Pacemakers & Artificial Organs
5240 Drug Delivery & Other Equipment
5299 Other Therapeutic (including defibrillators)
5310 Disposable Medical Products
5340 Handicap Aids
5350 Medical Monitoring Equipment
5380 Health related optics (incl. glasses, lenses)
5399 Other Medical/Health (NEC)
5410 Hospitals/Clinics/Primary Care
5420 Managed care (including PPO/PPM)
5429 Other Healthcare Facilities
5430 Emergency Services/Ambulance
5440 Hospital & Other Institutional Management
5499 Other Medical/Health Services
5510 Pharmaceutical Research
5520 Pharmaceutical Production
5530 Pharmaceutical Services
5540 Pharmaceutical Equipment
5550 Pharmaceuticals/Fine Chemicals (non-biotech)
5599 Other Pharmaceutical NEC
2320 Medical/Health
2325 Scientific
3700 Analytical & Scientific Instrumentation
4100 Human Biotechnology
4200 Agricultural/Animal Biotechnology
4300 Industrial Biotechnology
4400 Biosensors
4500 Biotech Related Research & Production Equipment
4600 Biotech Related Research & Other Services
4900 Other Biotechnology Related
5100 Medical Diagnostics
5200 Medical Therapeutics
5300 Medical Health Related Products
5400 Medical Health Services
5500 Pharmaceuticals
4000 Biotechnology and Pharmacology
5000 Medical/Health Related

Appendix 2: Industry Coding for SDC Platinum Rounds

IndustryDescription	IndCode
Advertising and Public Relations	services
Agricultural/Animal Biotechnology	biotech
Airlines and Aviation Related	services
Analytical & Scientific Instrumentation	device
Biochemical Products	biotech
Biosensors	device
Biosensors for Industrial Applications	device
Biosensors for Medical Diagnostic Applications	device
Biotech laser and optronic applications	device
Biotech Processes for Enhanced Oil Recovery/Mining	biotech
Biotech Processes for Food Industrial Applications	biotech
Biotech Processes for Pollution/Toxic Waste Contrl	biotech
Biotech Related Analytical Instruments & Apparatus	device
Biotech Related Animal Health & Nutrition Products	biotech
Biotech Related Commodity Chemicals	biotech
Biotech Related Fine Chemicals (NOT Pharmaceuts.)	biotech
Biotech Related Food Diagnostics	diagnostics
Biotech Related Food Enzymes and Cultures	biotech
Biotech Related Production Equipment	device
Biotech Related Research & Other Services	services
Biotech Related Research & Production Equipment	device
Biotechnology and Pharmacology	biotech
Business and Office Services	Services
CAD/CAM, CAE.EDA Systems	hcit
CAT Scanning	device
Chemical and Solid Material Recycling	services
Chromatographs & Related Laboratory Equipment	device
Communications/Networking Software	hcit
Computerized Billing & Accounting Services	services
Consulting Services	services
Data Processing,Analysis & Input Services	services
Database & File Management	hcit
Dependent Care (child care/assisted living	services
Diagnostic Services	services
Diagnostic Test Products & Equipment	diagnostics
Display Panels	hcit
Disposable Medical Products	device
Distributors,Importers and Wholesalers	services
DNA/RNA Probes	biotech
Drug Delivery & Other Equipment	device
Ecommerce Services	services
Educational Software	hcit
Emergency Services/Ambulance	services
Finance/Insurance/Real Estate products	hcit
Finance/Insurance/Real Estate Services	hcit
Financial Services,0ther	services
Genetic Engineering	biotech
Genetic. Eng. Microorganisms to raise plant yield	biotech
Genetically Engineered Animals	biotech
Genetically Engineered Plants	biotech
Graphics and Digital Imaging Software	hcit
Handicap Aids	device
Health & Beauty Aids	services
Health related optics (including glasses, lenses)	device
Holding Companies	services
Hospital & Other Institutional Management	services
Hospitals/Clinics/Primary Care	services
Human Biotechnology	biotech
Immune Response Effectors (interferons,vaccines)	biotech
In Vitro Monoclonal Antibody Diagnostics	biotech
In Vivo Monoclonal Antibody Diagnostics/Imaging	biotech
Industrial Biotechnology	biotech
Insurance Related	services
Integrated Turnkey Systems and Solutions	hcit
Internet Access Services and Service Providers	hcit
Internet/Web Design and programming services	hcit
Laser Related	device
Local Area Networks (incl. voice/data PBX systems)	hcit
Long Term Care/Home Care/Elder Care	services

IndustryDescription	IndCode
Managed care (including PPO/PPM)	services
Media Related Services	hcit
Medical Diagnostic Biotechnology Products	diagnostics
Medical Diagnostics	diagnostics
Medical Health Related Products	device
Medical Health Services	services
Medical Imaging	device
Medical Monitoring Equipment	device
Medical Therapeutics	biotech
Medical/Health	biotech
Medical/Health Info/Content	hcit
Medical/Health Related	diagnostics
Medical/Health Services	services
Medical/Health Software	hcit
Mobile Communications, Pagers & Cellular Radio	hcit
Nuclear Imaging	device
Other Analytical & Scientific Instrumentation	device
Other Animal Related Biotechnology	biotech
Other Animal Related Biotechnology	biotech
Other Biochemical Products	biotech
Other Biosensors	device
Other Biotech Process for Food/Industrial Products	biotech
Other Biotech Research & Production Equipment	device
Other Biotechnology Related	biotech
Other Biotechnology Services	services
Other Computer Services	hcit
Other Electronics Related (including keyboards)	hcit
Other Healthcare Facilities	services
Other Industrial Biotechnology	biotech
Other Measuring Devices	device
Other Medical Diagnostic Biotechnology	diagnostics
Other Medical Diagnostics	diagnostics
Other Medical Imaging	device
Other Medical/Health (NEC)	NEC
Other Medical/Health Services	services
Other Pharmaceutical NEC	biotech
Other Plant Related Biotechnology	biotech
Other Telephone Related	hcit
Other Therapeutic (including defibrillators)	device
Other Therapeutic Biotechnology	biotech
Other Therapeutic Proteins (incl. hormones & TPA)	biotech
Pacemakers & Artificial Organs	device
Packaging Products & Systems	services
Pharmaceutical Equipment	device
Pharmaceutical Production	device
Pharmaceutical Research	biotech
Pharmaceutical Services	services
Pharmaceuticals	biotech
Pharmaceuticals/Fine Chemicals (non-biotech)	biotech
Printing & Binding	services
Publishing	services
Publishing Services	services
Pure & Contract Biotechnology Research	biotech
Scientific	hcit
Scientific Info/Content	hcit
Scientific Products	hcit
Scientific Software	hcit
Security/Alarm/Sensors	hcit
Software Services	services
Surgical Instrumentation & Equipment	device
Surgical lasers (including laser delivery fibers)	device
Systems Software	hcit
Therapeutic Biotechnology Products	device
Therapeutic Monoclonal Antibodies	biotech
Therapeutic Services	services
Ultra Sound Imaging	device
Water Treatment Equipment & Waste Disposal Systems	services
X-Rays	device

Appendix 3: IPO Counts averaged for years 3-6 from vintage year

	num ipos avg year 3-6
1980	723.8
1981	660.5
1982	579.3
1983	503.5
1984	308.3
1985	242.5
1986	313.0
1987	418.8
1988	517.8
1989	567.5
1990	651.5
1991	645.3
1992	589.3
1993	574.0
1994	462.0
1995	332.5
1996	264.8
1997	154.3
1998	105.8
1999	134.3

From Ritter